A Manufacturing Energy and GHG Emissions Monitoring System – Supporting Eco-efficiency with Business Intelligence

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(Geliş/Received:12.05.2016; Kabul/Accepted:22.10.2016)
DOI: 10.17671/btd.11065

Abstract – Eco-efficiency is an emerging manufacturing trend aimed at improving manufacturing companies' sustainability balance sheets. Eco-efficiency practices focusing on energy or material flows are critical to reducing the environmental footprint of manufacturing processes of sustainable companies. This paper presents development of a new integrated energy and GHG emissions monitoring model and system that combines business intelligence (BI) with eco-efficiency to aid managerial decision making at various levels of a manufacturer. This combination enables near real-time calculation of eco-efficiency metrics key to green manufacturing companies, such as energy consumption/production output, and tracks the progress over time. By using critical BI techniques such as star-schema data models and contextualization, energy or GHG emissions associated with production activity can be allocated dynamically, and Key Performance Indicators (KPIs) such as value-added energy and non value-added energy can be calculated for eco-decision making.

Keywords – Eco-efficiency, energy monitoring, business intelligence, sustainable manufacturing

1. INTRODUCTION

At the fundamental level, eco-efficiency means, "doing more with less". World Business Council for Sustainable Development (WBCSD) first coined the term in 1991 and defines eco-efficiency as being "achieved by the delivery of competitively proceed goods and services that satisfy human needs and bring quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle, to a level at least in line with Earth's estimated carrying capacity". It is also expressed by the generic formula [1]:

Eco-efficiency = Economic value (added) / Environmental impact (added)

Five aspects of eco-efficiency have been identified in order to strategically implement in business:

1) Optimized processes for minimization of resources
2) Eco-innovation in manufacturing by using new knowledge to make old products more resource efficient to produce and use
3) Waste-recycling by using by-products of one industry as resources for another
4) Networks/virtual organizations for sharing resources thereby increase the effective use of physical assets
5) New services like leasing products which can spur a shift to product durability and recycling

In this regard, maximizing energy efficiency for processes and hence reducing carbon footprint lies in the heart of eco-efficiency. Current research in this aspect focuses on energy efficiency in manufacturing and reduction of GHG emissions by better quantifying and correlating energy consumption between production activities. From manufacturing point of view, there are three main drivers for energy efficiency initiatives: 1) Rising energy prices due to scarcity of the specific resources 2) New environmental regulations with their associated costs for GHG emissions, 3) Shift in customer purchase behavior with regard to "green" products and services [2]. Eco-efficiency, particularly energy consumption and related GHG emissions can be analyzed at two levels in a manufacturing company: 1) the plant, and 2) processes. In this context, direct energy is defined as the energy used by various manufacturing processes (such as turning, boring or painting) required to manufacture a part, whereas indirect energy is categorized as the energy consumed by activities in order to maintain the environment (such as lighting, heating or cooling) [3]. In essence, in a manufacturing facility, to provide high level of energy visibility, determination of energy performance indicators and effective energy metering is the key [4].

Gutowski et al. was the first to introduce an exergy framework in order to estimate unit process energy requirements for manufacturing processes [5]. Kara and Li further advanced this model by studying empirical models in order to characterize the relationship between unit energy consumption and process variables [6]. Their studies mainly relate Material Removal Rate (MRR) to Specific Energy Consumption (SEC) using an empirical equation with validation on four different machine tools for turning and milling operations. Avam and Xirouchakis developed a methodology for estimation of the variable energy requirements of a machine tool system (MTS) for part machining in 2.5D [7]. By reading APT files as an input, this method estimates the mechanical energy requirements of the spindle and feed axes with respect to 2.5D machining strategies (i.e. face, contour or pocket milling) by taking into account steady state and transition regimes of the MTS. Furthermore Rajemi et al. investigated optimum tool life for minimum energy of a turning process, revealing that optimum condition for minimum costs does not necessarily satisfy the minimum energy criterion [8]. Recently, in various other manufacturing processes, energy estimation is gaining attention as well. For instance Paralikas et al. developed a model to estimate energy efficiency of cold roll forming process [9]. Another research stream is making progress in energy measurement for process monitoring and energy optimization in eco-efficiency initiatives. One of the earliest microcomputer based energy monitoring system was developed by Yu et al. and named as EMOPIN. EMOPIN was able collect production and energy data from a plant and process them into meaningful indicators [10]. More recently, Vijayaraghavan and Dornfeld applied event stream processing techniques in order to automate the monitoring and analysis of energy consumption systems [11].

In addition to micro-planning, macro-planning approaches are also important for energy efficiency in order to characterize inter-process relationships of energy consumption during manufacturing. Vijayraghavan and Dornfeld suggested that value-added and non value-added discrimination is required for micro-level planning, and feature by feature analyses are necessary for macro-level planning to analyze energy at temporal scales [11]. Furthermore, Weinert et al. developed an energy-blocks methodology in order to create a macro-level planning framework for energy-efficient production systems [12]. By modeling each operating state of a manufacturing machine and its corresponding energy consumption, this method is intended to optimize a chain of processes with a sequence of operating states. Manufacturing system simulation, including relevant energy flows and related dynamics for all factory subsystems is also another key approach in macro-level modeling and what-if analyses of energy efficiency in manufacturing systems [13,14].

2. BUSINESS INTELLIGENCE IN MANUFACTURING

Business intelligence (BI) is a set of methodologies, processes, architectures, and technologies that transform raw data into meaningful and useful information for business-level users in order to support timely and correct decision making [15]. It can be defined as the ability to extract actionable insight from data available to the organization, both internal and external, for the purposes of supporting decision making and improving corporate performance [16].

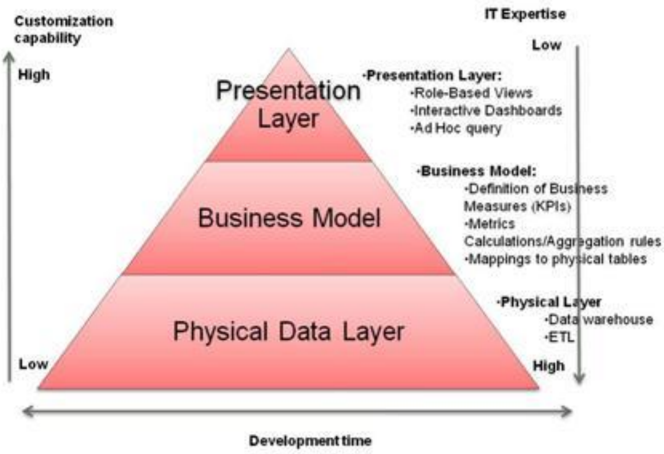

Figure 1. Layers of BI technology stack

Although what is known as business intelligence has been evolving over the last 35 years, in the 1990s, three technological enablers boosted BI applications and made BI a worldwide trend in IT. These are: data warehouse technologies, extract transform and load (ETL) tools, and powerful end-user analytical software with online analytical processing (OLAP) capabilities. Furthermore, the widespread adoption of internet tools and powerful user interface tools, such as OBIEE from Oracle, Business Object and NetWaver BI from SAP, SAS BI from SAS Institute ,and Cognos from IBM, enable business users to make informed business decisions with real-time data that can put a company ahead of its competitors [17]. Most BI vendors offer robust, scalable, well-integrated platforms with rich and broad BI functionality. However architecting and implementing enterprise BI solutions is still a complex and costly endeavor, and the goal of plug-and-play or out-of-the-box BI solutions remains elusive. Despite technological advances, for each BI implementation the most important critical success factor remains concept and metric definitions that underpin system architecture and analytics [18]. Hence sustainable production indicators that can be found in literature are major drivers and starting point of a BI architecture and implementation [19].

A typical BI system has three major components: a data warehouse for source data; business analytics, comprised of a collection of tools and business rules for manipulating, mining and analyzing the data in the data warehouse; and a user interface for performance monitoring (e.g., dashboards and KPI repositories) (Figure 1). Among these three technology stacks in a typical BI implementation, the presentation layer, with its role-based views and interactive dashboards, is the most customizable because modifying it requires the least amount of IT expertise and a relatively short amount of time. The development of a solid, yet expandable data warehouse requires advanced IT skills and usually takes the most time during a BI implementation. Business analytics, which serves as a middle layer between the data warehouse and the dashboards requires a level of expertise somewhere in between. However, its design is most critical, as it is the foundation for flexibility that enables development of various different dashboards requested by broad range of users.

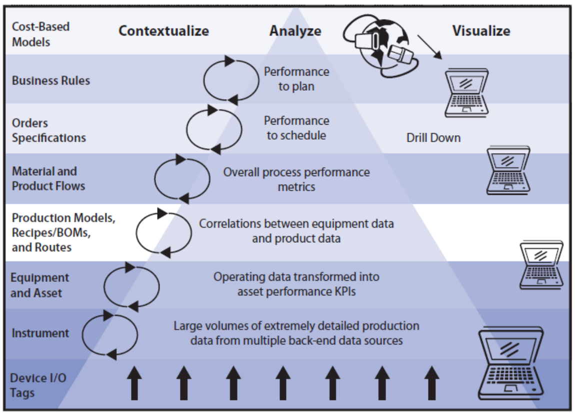

Figure 2. Core EMI capabilities [28]

Enterprise Manufacturing Intelligence (EMI) is a term introduced by AMR to describe emerging BI applications in the manufacturing domain that are designed to provide business owners and manufacturing managers a multi-site view of production performance and KPIs as opposed to standard speeds, feeds, and throughputs provided by traditional manufacturing performance reporting [21,22]. EMI frameworks can connect to and extract data from a highly diverse set of sources ranging from shop floor instruments, to historians (temporal data stores), to operational data stores and other relational stores. Core EMI capabilities are: 1) aggregation of data from a variety of real-time and back-end data sources; 2) contextualization of data elements from disparate sources such as process variables, product quality or yield data; 3) analysis of data by calculating a range of KPIs using raw process performance and cost-based information from ERP; and 4) visualization by providing an intuitive graphical representation of intelligence, enabling users to drill down from multi-plant representations to individual systems as required (Figure 2) (Smith , 2008b). Advanced process simulation, data mining and modeling applications are special cases of enterprise manufacturing intelligence.

The Sustainable Management Ecosystem model highlights three areas that relate directly to sustainable business practices [23]:

1) Environmental compliance: Historically, core activities include environmental health and safety, as well as labor regulations and philanthropy.
2) Communication: Companies must effectively communicate sustainability performance beyond their four walls.

3) Operational efficiency: Reduce GHG emissions by consuming green energy and reducing overall energy use.

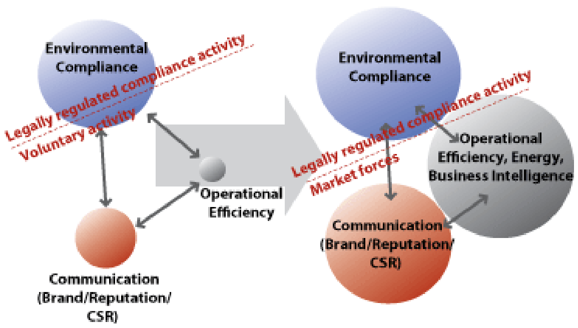

Figure 3. Forecasted shift in sustainability eco-system [23]

With pressure from increased legislation, significant improvement in energy efficiency can be achieved by upgrading EMI systems through a perfect marriage of energy efficiency and BI (Figure 3) [24]. Market analysis by AMR shows that operational and energy efficiency enabled by BI will grow significantly over the next decade [23].

3. An Integrated Energy and GHG Monitoring System: Sustainability Sensor Data Management

Our objective is to improve a manufacturing company's sustainability balance sheet by driving improvements in multiple dimensions such as organization, facilities and equipment hierarchy. With this goal in mind, we designed and developed an integrated energy consumption and GHG monitoring system that is compatible with several shop floor automation hardware vendors – Sustainability Sensor Data Management (SSDM).

SSDM offers comprehensive sustainability features:

1) Tracks multiple aspects of sustainability (e.g., electricity, gas, water, fuel) and calculates related costs and GHG emissions.
2) Directly integrates with meters, environmental management systems and building automation systems. Collects energy consumption and emissions data.
3) Allocates a GHG emissions inventory for any entity in an equipment, organization or facilities hierarchy via Virtual Metering.
4) Identifies specific opportunities for improving energy efficiency and reducing emissions using a navigation hierarchy.
5) Collects and correlates energy data with production activity. Enables reconfiguration of production system parameters to optimize energy consumption and reduce GHG emissions.
6) Includes out-of-the-box hierarchical dimensions, dashboards and KPI repositories, thereby minimizing customization time for SMEs.
7) Supports industry standard ISA-95 which defines integration models and terminology for enterprise and shop floor control systems.

3. AN INTEGRATED ENERGY AND GHG MONITORING SYSTEM: SUSTAINABILITY SENSOR DATA MANAGEMENT

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The manufacturing operations and sustainability data model is a model that complies with ISA-95. The data model is constructed as a hierarchical structure of entities such as sites and

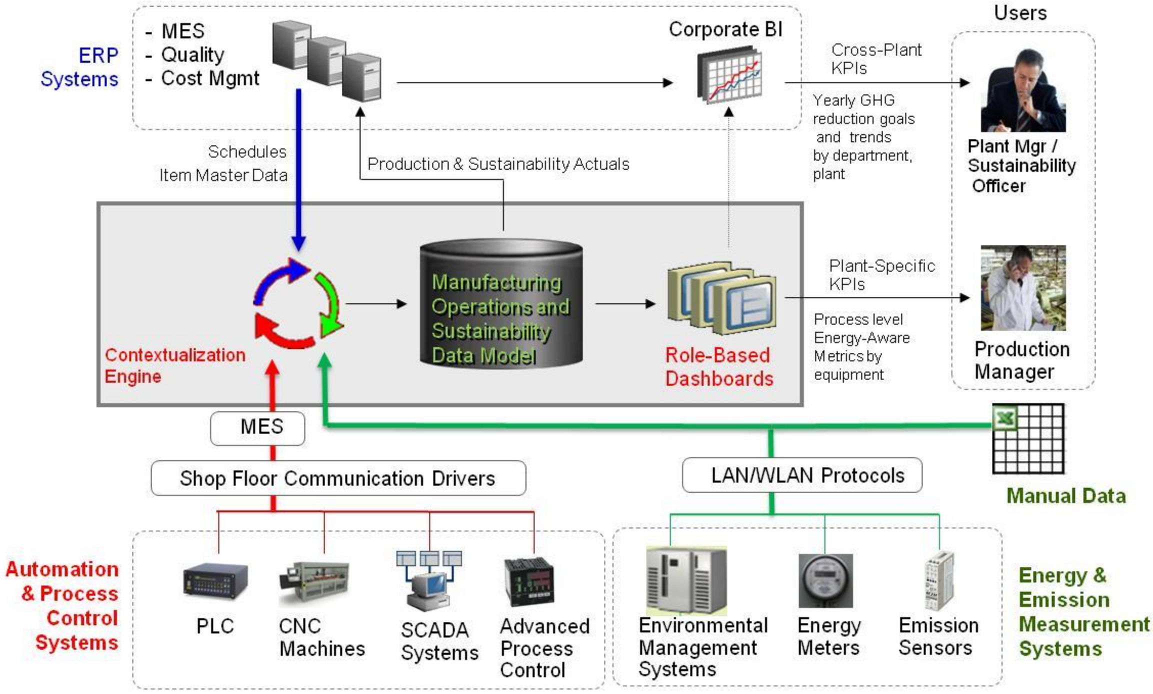

Figure 4. System architecture of SSDM

3.1. System architecture

The system architecture of SSDM provides flexibility and extensibility to enable rapid customization of rule-based dashboards at multiple levels of a factory (Figure 4). Here, we describe four major software components of the system:

1) Shop floor data collection modules
SSDM collects energy consumption information from energy and emission measurement systems as well as production activity information from shop floor automation and process control systems. Energy and emission measurement systems include environmental management systems, energy meters, and emission sensors. Shop floor systems include programmable logic controllers, CNC machines, robot controllers, etc.
2) Contextualization engine
SSDM includes a contextualization engine that correlates production data from the automation and process control systems with energy consumption data from the energy and emission measurement systems. This correlation provides important contextual information to better inform energy management decisions. The contextualized energy consumption data are presented as KPIs.
3) Sustainability data model

equipment. Users of the manufacturing operations and sustainability data model can model a specific manufacturing operation using the hierarchy.

4) Role-based dashboards
Data provided by the various components of the hierarchy are stored in the manufacturing operations and sustainability data model so that summaries, such as dashboards reflecting current manufacturing operational conditions, can be provided. End users of the energy management system include personnel at various levels in the enterprise from corporate management to production floor.

3.2. Data Collection from Shop Floor, Real and Virtual Metering

Several different types of machines and controllers typically can be found on an automated manufacturing shop floor. Most modern machine controllers have built-in communication capability based on industrial communication standards or protocols. A variety of protocols have been developed for shop floor communication, and manufacturing companies have adopted many general purpose communication protocols as well. Manufacturing automation protocol (MAP), FieldBus, ProfiBus, RS-232, RS-485, local area networks (LANs) and wireless networks (WLANs) based on transmission control protocol/Internet protocol (TCP/IP) are among the most common and widely-used standards on shop floors [25]. SSDM directly receives data via an open TCP/IP protocol port for importing incoming raw data into tables. Whether it is an automation/process control system or energy/emission measurement system, SSDM sets itself apart from proprietary internal hardware systems or standards-based communication protocols by using a simple TCP/IP port to receive data. To be compatible with SSDM, a

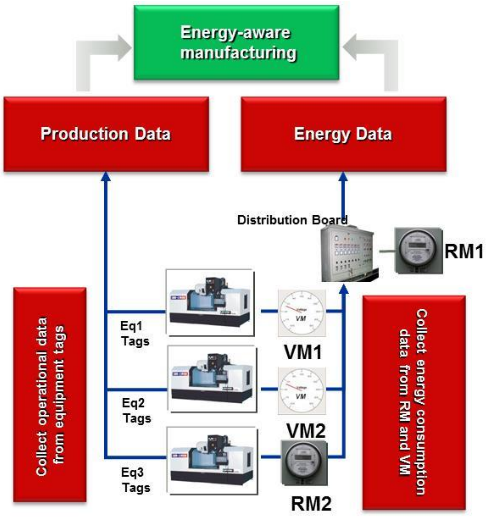

Figure 5 Virtual and Real Metering

hardware vendor must provide an add-on module enabling data transmission through a specified TCP/IP port.

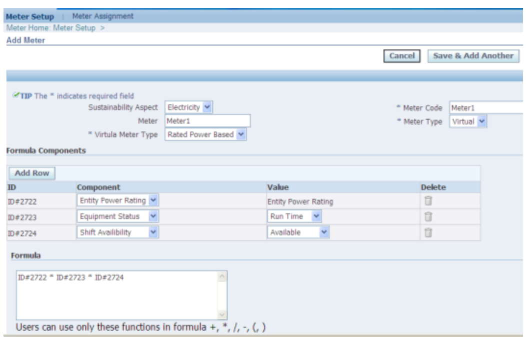

Figure 6. User interface for meter definition

Energy data for any equipment is collected via smart meters attached to power line. Ideally, every manufacturing machine at shop floor level should have a smart meter connected, if detailed analysis of its consumption is required. This approach which is also called sub-metering, may not be possible for each machine because of cost reasons. With a new approach developed for SSDM, some of the machines, which are usually non-critical, can be estimated. This approach, called "Virtual Metering" presents two methods for estimation of energy consumption of an equipment without a physically attached meter.

1) Based on aggregation of other meters data in same network. For instance in Figure 5 Virtual Meter 1and 2 can be calculated by -VM1,2= (RM1 – RM2)/2

2) Based on power rating of the equipment. For instance in the same figure, alternatively Virtual Meter 1 can be estimated by VM1= Power Rating-Equipment_1 * Operation Time. A user interface for defining a Virtual Meter is also depicted in Figure 6.

3.3. Energy and Emission Contextualization

One of the difficult tasks of Life Cycle Assessment is allocating measured consumption or emissions to production activity both accurately and efficiently [26]. The problem is illustrated in Figure 7 with a steel manufacturing process where beams and bars are two different product outputs of the same process and 3 kg CO^2 are emitted from that process each hour. In addition, production orders for beams and bars are completely random, and at different dimensions and grades. Thus, accurately allocating CO^2 emissions or energy consumption to each single bar or beam is not a trivial problem to solve.

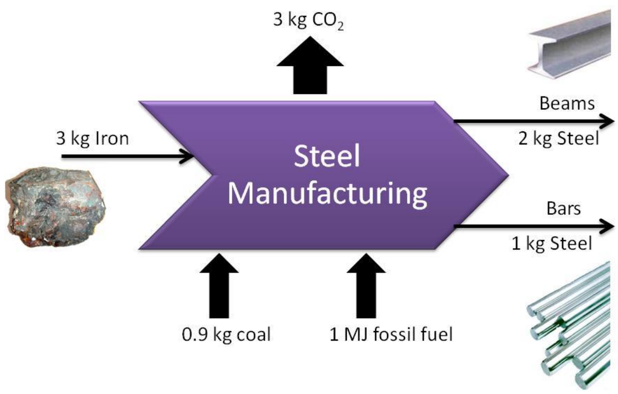

Figure 7. CO^2 allocation in steel manufacturing

In a manufacturing environment where thousands of part mixes are processed in hundreds of different machining centers, allocation problems become quite complicated. In order to simplify this problem utilizing technological tools, SSDM includes a contextualization engine that correlates production data from the automation and process control systems with energy consumption data from the energy and emission measurement systems (Figure 8). This correlation provides important contextual information to better inform energy management decisions. The contextualized energy consumption data are presented as value-added/non value-added energy KPIs and direct/indirect energy consumption KPIs.

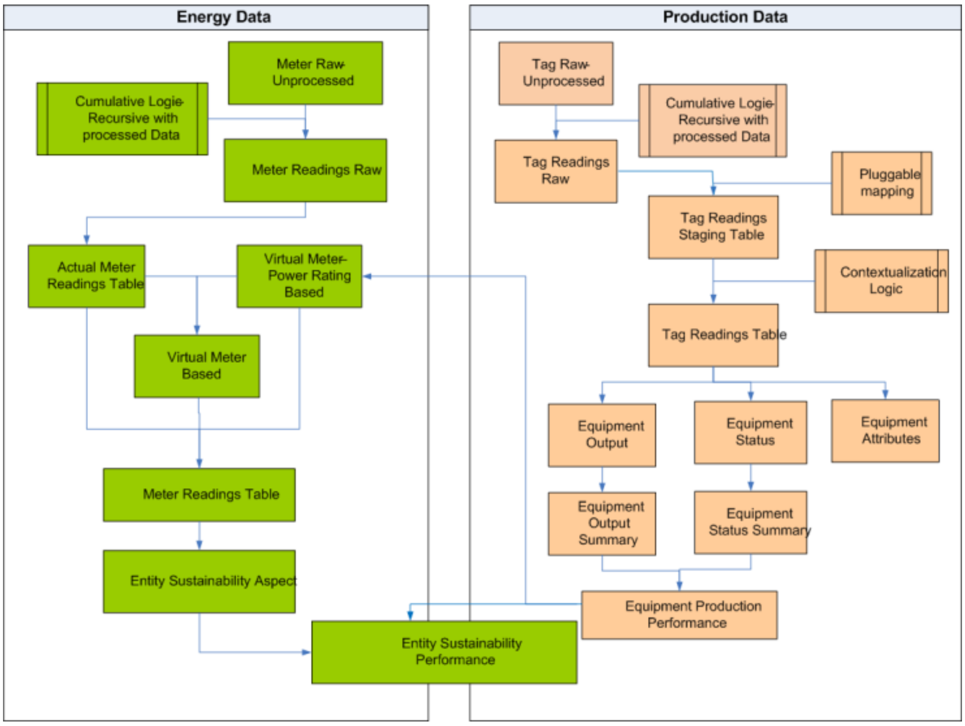

Figure 8. Energy contextualization process

4. DATA MODEL

4.1. Dimensional Modeling

Dimensional modeling is a data modeling technique for delivering BI data as it addresses the twin non-negotiable goals of business knowledge and fast query performance [27]. Dimensional modeling divides the domain into measurement and context. Measurements are captured by the organization's business processes and their supporting operational source systems. Measurements are usually numeric values, referred to as facts. Facts are largely contextual, and are true for the moments at which they were recorded. This context is divided into independent logical clumps called dimensions. Dimensions describe the who, what, when, where, why and how of the measurement. Each organizational process can be represented by a dimensional model that consists of a fact table containing numeric measurements such as meter readings from a smart meter surrounded by several dimensional tables containing the textual context, as shown in Figure 9. Dimensional models stored in a relational database platform are typically referred to as star schemas; dimensional models stored in multidimensional OLAP structures are called cubes.

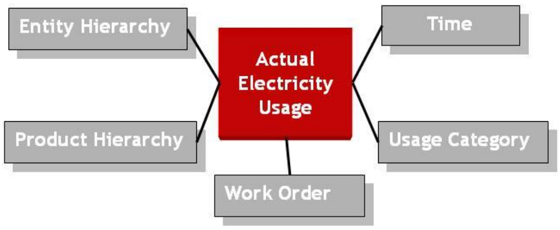

Figure 9. Star schema actual electricity usage

4.2. Normalized Modeling

Third normal form (3NF) is quite different from dimensional modeling. It is a design technique that seeks to eliminate data redundancies, whereas dimensional modeling seeks high query performance rather than redundancy. Typical ERP systems contain thousands of entities that translate into physical tables in relational databases. The software industry commonly refers to 3NF models as entity relationship (ER) models. ER diagrams use boxes and lines to communicate the relationships between tables. Both 3NF and dimensional models can be represented as ER diagrams because both consist of joined relational tables; the key difference is the degree of normalization.

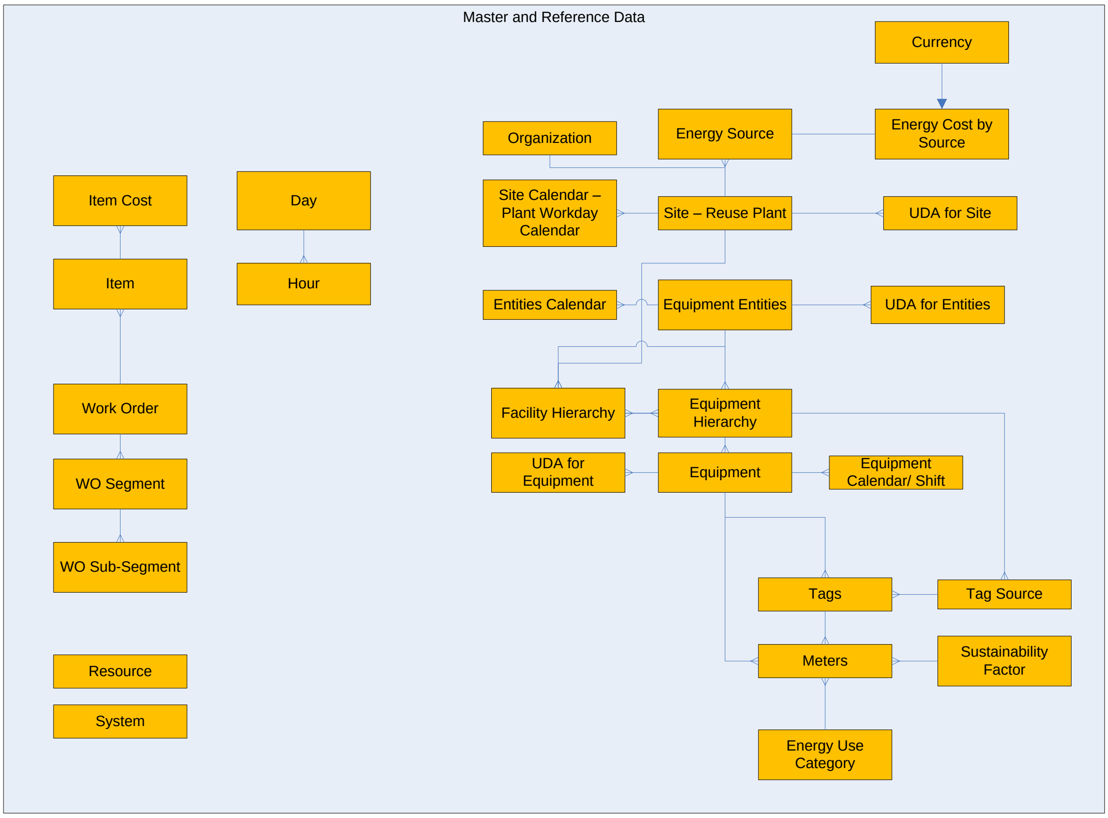

Figure 10 Data model of SSDM

The SSDM data model is a hybrid model containing tables with star schemas and 3NF forms. While operational data pertaining to energy measurement in production or GHG emissions are stored in star schemas, master and reference data such as equipment, facility hierarchies, meters and associated tags are modeled and stored in 3NF tables (Figure 10).

5. DASHBOARDS AND SCORECARDS

Dashboards and scorecards usually consist of a combination of reports and charts that visualizes exception handling and provide drilldown data analysis capabilities for multiple business applications. Designed to deliver historical, current, and predictive information typically represented by KPIs, dashboards use visual cues to focus user attention on important conditions, trends, and exceptions [17]. Unlike standard reporting tools, they are highly customizable, even by executive users. Common themes across these reporting applications are information consolidation, exception highlighting, ease of use, and role-based customization flexibility at multiple organization levels.

Out-of-the-box green SSDM provides multiple KPIs used to account for and report carbon emissions, monitor electricity consumption and estimate energy costs. Role-based dashboards can be customized to present appropriate information for manufacturing executives or managers of a green-oriented organization (Figure 11).

Leveraging the green intelligence provided by SSDM, sustainability managers are able to identify opportunities for energy efficiency and reduction of carbon emissions, hence realizing their corporate goals towards eco-efficient manufacturing. The key to identifying opportunities is an ability to isolate bottlenecks by drilling down through the KPIs. Oracle's OBIEE technology (the basis for SSDM dashboards and ad-hoc analysis tools) provides a dynamic capability to drill down from top-level entities (i.e., site, building, department) to bottom-level entities (i.e., manufacturing equipment, lighting, compressors, etc.) in order to isolate eco-efficiency bottlenecks. The list of out-of-box SSDM KPIs designed specifically for tracking common green initiatives, which can be categorized into three groups.

1) Absolute KPIs measure total quantities, such as actual electricity usage, annual changes in electricity usage, or planned CO2 emissions.

Figure 11. SSDM production manager dashboard

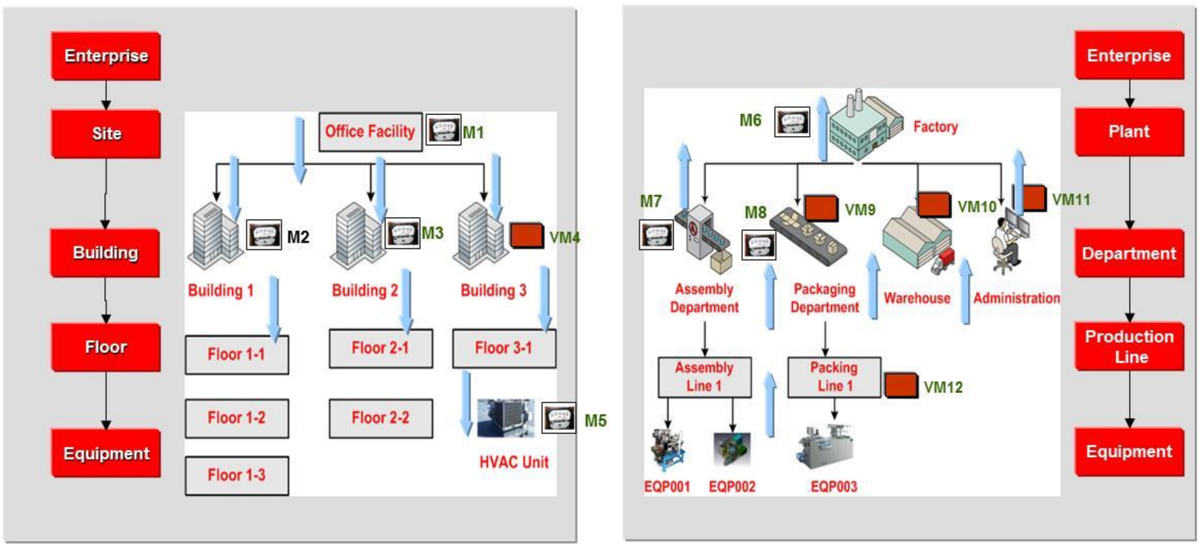

Figure 12. Flexible entity modeling and hierarchies

2) Relative KPIs normalize absolute KPIs against some entity attribute, such as an enterprise or a product (i.e., Actual Electricity Usage per Headcount or Electricity Cost per Unit of Output).

3) Contextualized KPIs are calculated by the contextualization engine (i.e., Value-Added Energy Percentage for a product, or Total Energy Consumption by Direct Usage for an organization.

5.1.Role based decision making with flexible entity modeling and hierarchies

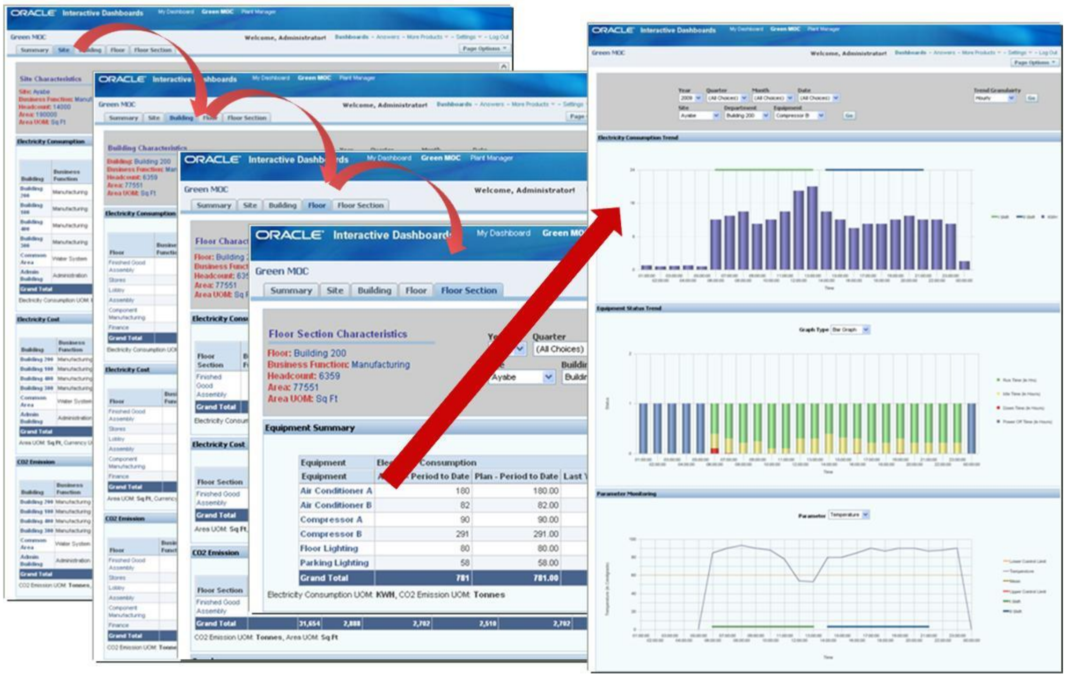

Figure 13. Drill-down from site to equipment

SSDM's design objective is to aid managerial decision making at various levels of an enterprise. Therefore it has to have a flexible entity modeling architecture where enterprise layers can be configured for different organizational or physical scenarios. Figure 12 demonstrates two scenarios where data can be aggregated from bottom-up or allocated from top to bottom. Left side is model of a physical scenario where an enterprise is modeled based on its physical hierarchy. High level measurements can be allocated to bottom layers by Virtual Metering. This configuration is optimum for helping decision making of facilities managers or corporate sustainability officers. On the right side, an organizational model can be seen with a production focus. Low level data collected from instruments can be aggregated to upper layers and Virtual Meters are used for estimation of entities where direct measurement is not available. Several production departments are comprised of production lines and equipment. At department level, production and operation managers can analyze their respective department's sustainability. As department add up to plants and enterprise itself at these levels, VP of Operation or Production is capable of viewing aggregated data for comparison and analysis of several plants and departments.

Figure 13 shows OBIEE dashboards of a hierarchy where system is configured based on facilities. In order to analyze and isolate high energy consumption at a site, a facilities manager can start drilling from top level, viewing the aggregated energy consumption of all sites and go down though all layers until he can analyze individual equipment consumption against activity. All this analysis can be performed dynamically by OBIEE dashboards.

6. ANALYSIS OF VALUE/NON-VALUE ADDED ENERGY

The most common energy sources used on shop floors are electricity and natural gas. Electricity is mostly used in machining centers, for equipment such as robots and conveyors. Natural gas is most commonly used in processes such as heat treatment or paint drying where extensive heat is necessary. For machining processes we can consider electricity as main major source of power. In this case, energy charges were based on direct electricity consumption in kWh (kilowatt-hours) during the electricity consumption period. Demand was measured in kWs (kilowatts) or kVAs (kilovolt-amperes), which is instantaneous power consumed by equipment. In order to make the analysis rigorous enough, the data model can store down to 10-second demand intervals. However, since this level of detail increased the amount of data, demand was usually aggregated to a 1-minute scale.

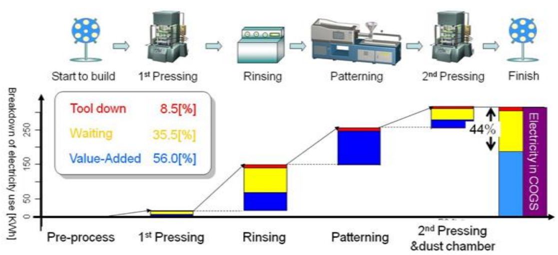

Figure 14. Value-added and non value-added energy

The energy model was used to calculate total energy used in a manufacturing line. Total energy consumed has two components. The first is value-added energy

(VAE), or the energy consumed during an actual machining operation such as cutting, drilling or boring. The energy aggregated as VAE must be consumed during the "RUN" state for machining equipment. The second type of energy is non value-added energy (NVAE), or energy consumed during "IDLE," "DOWN," or "ALARM" machining equipment states. Omron Corp., a development partner of SSDM, found that 56% of electricity consumed in their production facilities was VAE (Figure 14).

$$E_{Total} = VAE + NVAE$$

VAE = Value-Added Energy
NVAE = Non Value-Added Energy

Use Case I – Energy by Machine Tool
Figure 15 depicts hypothetical energy readings for a CNC and its states of IDLE, DOWN, and RUN. For this simple scenario, the contextualization algorithm yields VAE = 3250 KWh, NVAE= 390 and VAE% = 89.3.

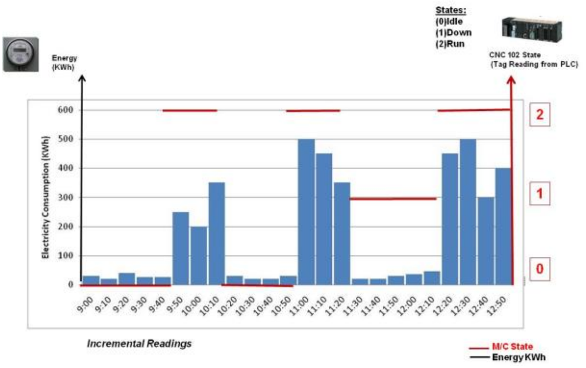

Figure 15. VAE and NVAE use case by machine tool

Use Case II - Energy by Work Order

The aforementioned case illustrates VAE and NVAE aggregated by machining centers on a shop floor. A part's total energy consumption or emissions aggregation must be calculated based on the work order of the part. For the case illustrated in Figure 16, two work orders, WO-101 and WO-102, are manufactured on CNC-102 between the hours of 9:00 and 13:00. WO-101 is for part "Shaft-502" and five items are processed for operation step 30 on CNC-102 between 9:00 and 10:30. For WO-102, "Shaft-1050," three items are processed for operation step 30 between 10:50 and 13:00.

VAE and NVAE for each work order on CNC-102, and energy consumed for each part are tabulated in Table 1.

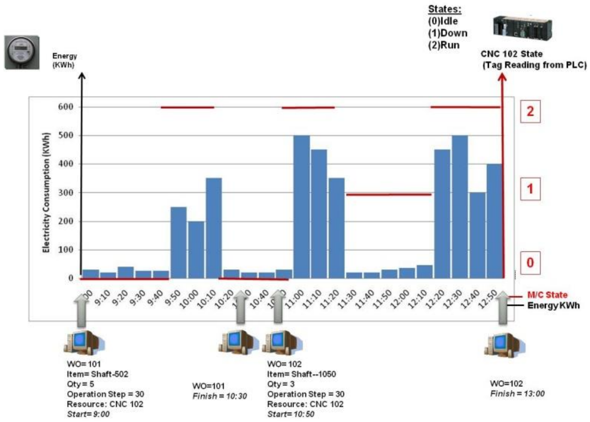

Figure 16. VAE and NVAE use case by work order

Table 1. VAE and NVAE Calculations for Use Case II

WO-101						WO-102				
Time	Data	Status	VAE(kWh)	NVAE(kWh)		Time	Data	Status	VAE(kWh)	NVAE(kWh)
9:00	30	IDLE		30		10:50	30	IDLE		30
9:10	20	IDLE		20		11:00	500	RUN	250	
9:20	40	IDLE		40		11:10	450	RUN	200	
9:30	25	IDLE		25		11:20	350	RUN	350	
9:40	25	IDLE		25		11:30	20	DOWN		20
9:50	250	RUN	250			11:40	20	DOWN		20
10:00	200	RUN	200			11:50	30	DOWN		30
10:10	350	RUN	350			12:00	35	DOWN		35
10:20	30	IDLE		30		12:10	45	DOWN		45
Total Between 9.00 - 10.30			800	170		12:20	450	RUN	450	
VAE%			82.5			12:30	500	RUN	500	
						12:40	300	RUN	300	
No-context energy						12:50	400	RUN	400	
10:30	20	IDLE		20		Total Between 10.50 - 13.00			2450	180
10:40	20	IDLE		20		VAE%			93.2	

7. ENERGY CONTEXTUALIZATION AND VISIBILITY

Data collection capabilities of SSDM was validated by a laboratory set-up. We developed this set-up with Mitsubishi's North America Automation Division, which supplies automation hardware. The lab set-up has the following four major components:

1) Mitsubishi PLC and HMI hardware
2) Windows Server
3) Windows Client
4) An AC electric motor and controller

The configuration of the shop floor validation system is provided in Figure 17. For shop floor hardware simulation, a Mitsubishi PLC Controller with an attached e-Factory module is used. The e-Factory module, developed by ILS Corp., is capable of sending all PLC tag readings to the SSDM data warehouse via a TCP/IP Ethernet port. An HMI screen simulating three machine tools, a drilling machine, a CNC machining center and a grinding machine, as well as a barcode reader for user inputs is connected to the PLC. For each machine tool, it is possible to download work orders from the ERP system, perform a simulated run of each work order, and monitor machine tool statuses such as UP, IDLE or DOWN. Errors can be generated randomly, which puts the machines in downtime, scraps some quantities in the work order and completes the rest. The CNC machining center is connected to a DC motor that measures its real energy consumption, and the other two machine tools generate simulated energy consumptions. The results of the experimental shop floor are displayed on a custom dashboard where Energy, Cost of Energy, VAE, NVAE, VAE% and Consumption per Output are displayed numerically. Distribution of CO2 emissions can be also be viewed as pie chart. Correlations between production activity and energy consumption, and CO^2 emissions and operation parameters (e.g., temperature) are displayed as trend graphs in order to demonstrate the detailed analysis capabilities of SSDM (Figure 18).

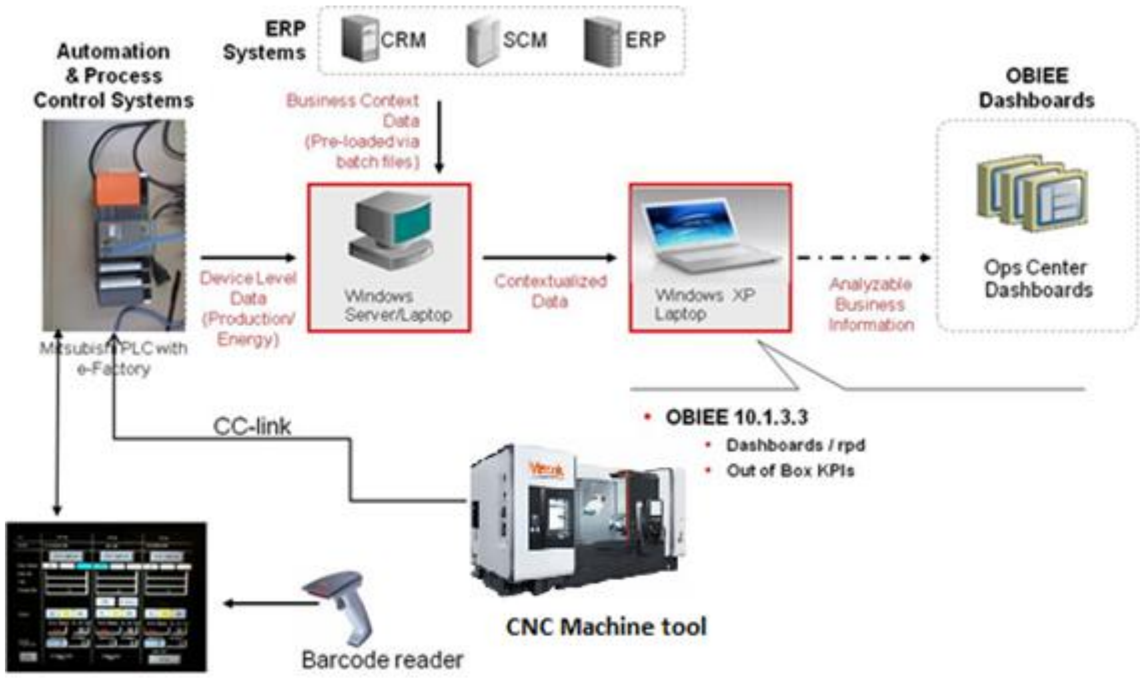

Figure 17. Set-up for validation of SSDM

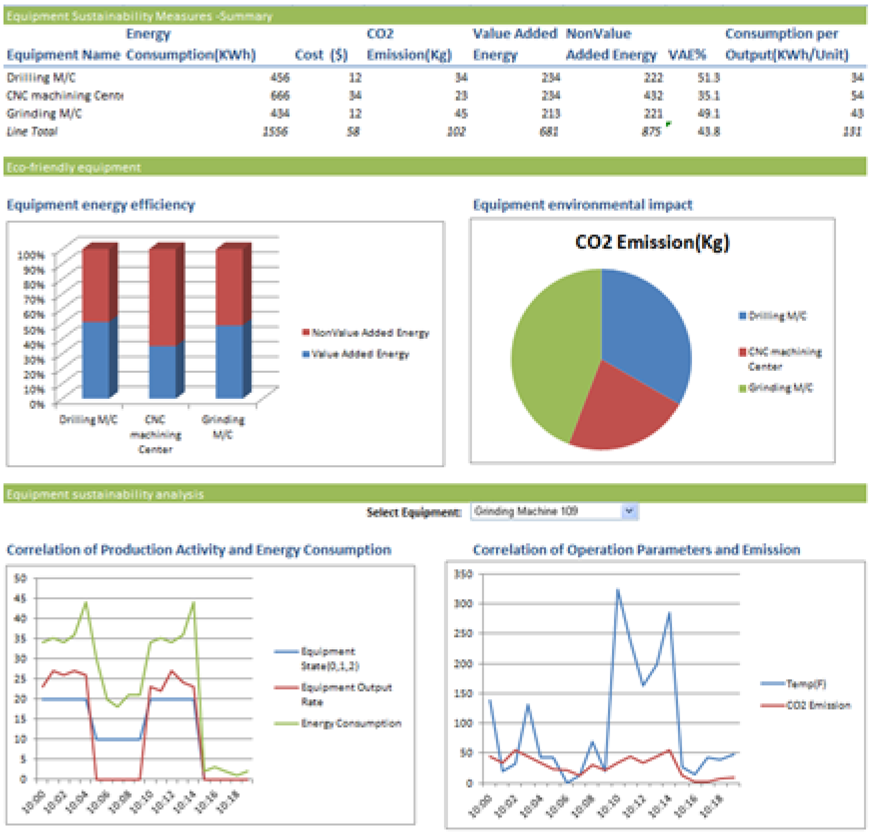

Figure 18. Dashboard and sample KPIs for lab set-up

8. CONCLUSION

This work extends enterprise manufacturing intelligence to the sustainability domain in order to support eco-efficiency initiatives of production companies. We have attempted to develop an integrated system model with hardware and software infrastructure that can measure energy consumption, GHG emissions and production activity. Using advanced BI technologies, the main contribution of this study lies in the contextualization of energy usage data with production activity in order dynamically generate KPIs such as VAE and NVAE. This capability promises to support and accelerate energy and emissions studies with fast and accurate real data that aims to improve eco-efficiency for manufacturing companies.

Business Intelligence enables availability of the right information to the right people at the right time. This is the key to successful decision making for continuous improvement towards sustainability. SSDM's closed loop execution between manufacturing management and shop floor systems can be achieved by:

- Setting goals and objectives for improving eco-efficiency
- Establishing plans to achieve the goals
- Monitoring actual eco-efficiency performance against the goals and objectives
- Taking corrective actions

Future work includes addition of eco-efficiency metrics on material flows, and also addition of more contextualized KPIs which can enable accurate calculation of embodied energy and carbon emissions along product dimension.

ACKNOWLEDGEMENTS

The author is thankful to Amit Singh, Giri Tippireddy, Yong Feng, Aravindan Sankaramur, Yasushi Okamura, and Andy Binsley of Oracle Inc. for their collaboration and contributions to this work. Also special appreciation goes to Mitsubishi North America Automation Division for realization of test set-ups of SSDM.

REFERENCES

[1] S. Erkko, M. Melanen, P. Mickwitz, "Eco-efficiency in the finish EMAS reports –a buzz word?", J. of Cleaner Production, 13(8), 799-813, 2005.
[2] K. Bunse, M. Vodicka, P. Schonsleben, M. Brulhart, F. O.Ernst, "Integrating energy efficiency performance in production management – gap analysis between industrial needs and scientific literature", J. of Cleaner Production, 19(6-7), 667-679, 2011.
[3] S. Rahimifard, Y. Seow, T. Childs, "Minimizing Embodied Product Energy to support energy efficient manufacturing", CIRP Annals – Manufacturing Technology, 59(1), 25-28, 2011.
[4] E. O'Driscoll, D.O. Cusack, G.E. O'Donnell, "The development of energy performance indicators within a complex manufacturing

facility", Int. J. Advanced Manufacturing Technology, 2013, 68(9), 2205-2214, 2013.
[5] T. Gutowski, J. Dahmus, A. Thirieaz, "Electrical Energy Requirements for Manufacturing Processes", 13th CIRP international Conference on Life Cycle Engineering, Leuven, May 31st – June 2nd , 2006.
[6] S. Kara, W. Li, "Unit process energy consumption models for material removal processes", CIRP Annals – Manufacturing Technology, 60(1), 37-40, 2011.
[7] O.L.Avram, P. Xirouchakis, "Evaluating the use phase energy requirements of a machine tool system", J. of Cleaner Production, 19 (6-7), 699-711, 2011.
[8] M.F. Rajemi, P.T. Mativenga , A. Aramcharoen, "Sustainable machining: selection of optimum turning conditions based on minimum energy considerations", J. of Cleaner Production, 18(10-11), 1059-1065. 2010.
[9] J. Paralikas, K. Salonitis, G. Chryssolouris, "Energy efficiency of cold roll forming process", Int. J. Advanced Manufacturing Technology, 66(9), 1271-1284, 2013.
[11] Z.Z. Yu, S.N. Tay , W.G. Cartwitgh, "A computer-based energy monitoring program for industry: EMOPIN", Computers in Industry, (13)2, 155-167, 1989.
[12] A. Vijayaraghavan, D. Dornfeld, "Automated energy monitoring of machine tools", CIRP Annals – Manufacturing Technology, 59(1), 21-24, 2010.
[13] N. Weiner, S. Chiotellis, G. Selinger, " Methodology for planning and operating energy-efficient production systems", CIRP Annals – Manufacturing Technology, 60(1), 41-44. 2011.
[14] C. Hermann, C. Thiede, S. Kara, J. Hesselbach, " Energy oriented simulation of manufacturing systems – Concept and application", CIRP Annals – Manufacturing Technology, 60(1), 45-48, 2011.
[15] J. Moon, K. Shin, J. Park, "Optimization of production scheduling with time-dependent and machine-dependent electricity cost for industrial energy efficiency", Int. J. Advanced Manufacturing Technology, 68(1), 523-535, 2013.
[16] E. Turban, J.E. Aronson , T.P. Liang, R. Sharda , Decision Support and Business Intelligence Systems, Eight edition, Pearson international, 2011.
M.Canes , Business intelligence for the SME, CA magazine, 46-48, September 2009.
[17] B. Evelson, The Forrester Wave: Enterprise Business Intelligence Platforms, Q3 2008, Forrester research, Jul 31, 2008.

[18] D. Grigori, F. Casati, M. Castellanos, U. Dayal , M. Sayal, M. Shan, "Business Process Intelligence", Computers in Industry, 53(3), 312-343, 2004.
[19] V. Veleva, M. Ellenbecker, "Indicators of sustainable production: framework and methodology", J. of Cleaner Production, 9(6), 519-549, 2001.
[20] A. Smith, "From EMI to Operations Intelligence, Part 1: Business Leaders Seek Key Performance Drivers", Manufacturing Operations 2008 Landscape Series, AMR Research, 2008.
[21] D.M. Kroenke, Using MIS, 4th Edition, Pearson, 2012.
[22] A. Smith, "From EMI to Operations Intelligence, Part 2: Choosing the Best Mix of Applications for Your Manufacturing Scenario", Manufacturing Operations 2008 Landscape Series, AMR Research, 2008.
[23] S. Stokes, "Sustainability, Green, and the Greenback, Where's the Money in a Sustainability Management Ecosystem", AMR research, 2009.
[24] H. Fernando, "Nine Sustainability Trends to Watch Out For", AMR Research, 2010.
[25] T.-C. Chang, R.A. Wysk , H.-P. Wang, Computer Aided Manufacturing, 3rd edition, Prentice Hall , 2006.
[26] The Greenhouse Gas Protocol, A corporate accounting and reporting standard, WBCSD/WRI, Available at: http://www.ghgprotocol.org/ standards/corporate-standard, 2004.
[27] R. Kimball, M. Ross, W. Thornthwaite, J. Mundy, B. Becker, The data Warahouse Lifecycle Toolkit, 2nd edition, Wiley, 2008.
[28]S. Jacobson, "Enterprise Manufacturing Intelligence: The missing Link Between Product Supply and Demand Fulfillment", AMR Research, 2009.